ULTRASOUND IMAGE RECONSTRUCTION AND DISPLACEMENT TRACKING

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Abstract: *Ultrasound imaging unlocked the analysis of rapidly changing physical phenomena in the human body, with new applications such as ultrasensitive flow imaging in the cardiovascular system or shear-wave elastography. The accuracy achievable with these motion estimation techniques is strongly contingent upon two contradictory requirements: high quality of consecutive frames and a high frame rate. Increasing the number of steered ultrafast acquisitions the image quality will be achieved but at the expense of a reduced frame rate and possible motion artifacts. To achieve accurate motion estimation at uncompromised frame rates and immune to motion artifacts, the proposed approach relies on single ultrafast acquisitions to reconstruct high-quality frames with the help of the new technologies. To this end, a convolutional neural network-based image reconstruction method combined with a hybrid KNN model is deployed. The proposed approach will surely unlatch the full capability of ultrafast ultrasound, in applications such as ultrasensitive cardiovascular motion.*

Keywords: DenseNet Architecture, Hybrid KNN, Medical Image Processing.

1. INTRODUCTION

Ultrasound imaging enables reconstructing full-view images from single acquisitions by capturing the entire field of view at once, using unfocused transmit wavefronts such as plane waves (PWs) or diverging waves (DWs). Imaging large tissue regions in ultrasound imaging at higher frame rates are necessary for studying the most rapidly changing physical phenomena in the human body. In the cardiovascular system, where a frame rate of several hundred hertz is needed for resolving tissue motion and flow patterns accurately, ultrafast imaging enables increased ensemble lengths, improving the robustness and sensitivity of displacement estimates significantly. A method for reconstructing high-quality ultrasound images is introduced from single unfocused acquisitions[10]. It consists of a back projection-based DAS operation followed by the application of a convolutional neural network (CNN), specifically trained to reduce the diffraction artifacts inherent to the deployed ultrafast ultrasound imaging setup. Image processing is the step taken to process images before they are used by model training. This includes resizing, orienting and color corrections in images. Preprocessing is a required process to achieve good results for the model training applications. For example, in fully connected layers in CNN require all the images taken for training must be in the same sized arrays.

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I. 2. LITERATURE SURVEY

Perdios *et al.* [6] proposed an approach that consists of a CNN trained to restore high-quality images from single unfocused acquisitions and a speckle tracking algorithm to estimate inter-frame displacements from two consecutive frames only. Compared with conventional multi-acquisition strategies, this approach is immune to motion artifacts and enables accurate motion estimation at maximum frame rates, even in highly heterogeneous tissues prone to strong diffraction artifacts.

James *et al.* [8] proposed a training mode that optimizes three different tasks: 1) image artifacts detection, 2) artifact correction, and 3) image segmentation. The reconstruction network was trained to automatically correct motion-related artifacts using synthetically corrupted cardiac MR k-space data and uncorrected reconstructed images. Using a test set of 500, 2D+time cine MR acquisitions from the UK Biobank data set, demonstrably good image quality and high segmentation accuracy in the presence of synthetic motion artifacts are achieved.

Zhao *et al.* [1] proposed a model for image reconstruction of ultrasound computed tomography based on the wave equation that is able to show much more structural details than simpler ray-based image reconstruction methods. However, to invert the wave-based forward model is computationally demanding. To address this problem, an efficient fully learned image reconstruction method was developed based on a convolutional neural network. The image is reconstructed via one forward propagation of the network given input sensor data, which is much faster than the reconstruction using conventional iterative optimization methods. To transform the ultrasound measured data in the sensor domain into the reconstructed image in the image domain, multiple down-scaling and up-scaling convolutional units are applied to efficiently increase the number of hidden layers with a large receptive and projective field that can cover all elements in inputs and outputs respectively. For dataset generation, a paraxial approximation forward model is used to simulate ultrasound measurement data

D. Boukerroui [3] proposed ultrasound segmentation methods, in a broad sense, focusing on techniques developed for medical B-mode ultrasound images. A review of articles by clinical application is presented to highlight the approaches that have been investigated and the degree of validation that has been done in different clinical domains. Then, a classification of methodology in terms of the use of prior information is presented. Finally, selecting ten papers that have presented original ideas that have demonstrated particular clinical usefulness or potential specific to the ultrasound segmentation problem.

3. PROPOSED SYSTEM

In this system, the proposed image reconstruction method considered relies on PW acquisitions which are performed without transmitting apodization. Single PW acquisitions with normal incidence are used in the proposed CNN-based image reconstruction method. For each transmit-receive event, echo signals are recorded on all transducer elements. An approach for estimating 2-D inter-frame displacements at maximum frame rates is proposed, by combining our CNN-based image reconstruction method with a state-of-the-art hybrid KNN algorithm. Although estimating the axial displacement remains the standard in ultrasound imaging, deep learning-based estimation is increasingly gaining attention in both flow and tissue motion applications, as it enables the analysis of more complex motion patterns. In elastography, 2-D displacement maps may be of interest to increase the quality and robustness of the estimated elasticity maps. Also, the deep learning model represents an optimal fit for high-frame-rate displacement estimation since, unlike vector doppler techniques, it does not rely on multi-angle acquisitions. Moreover, the deep learning-based estimation can be performed accurately from two consecutive frames only, whereas doppler-based techniques usually require multiple consecutive frames to estimate the phase accurately. The input dataset used the ultrasound images of the abdominal region. These images are generated by taking the number of frames from an ultrasound scanning video. These images are trained with the DenseNet module to efficiently reconstruct the input image. The input image is projected using a back projection algorithm. The projected image is fused with the trained input image and the displacement is tracked. Figure 1 shows the workflow of the system.

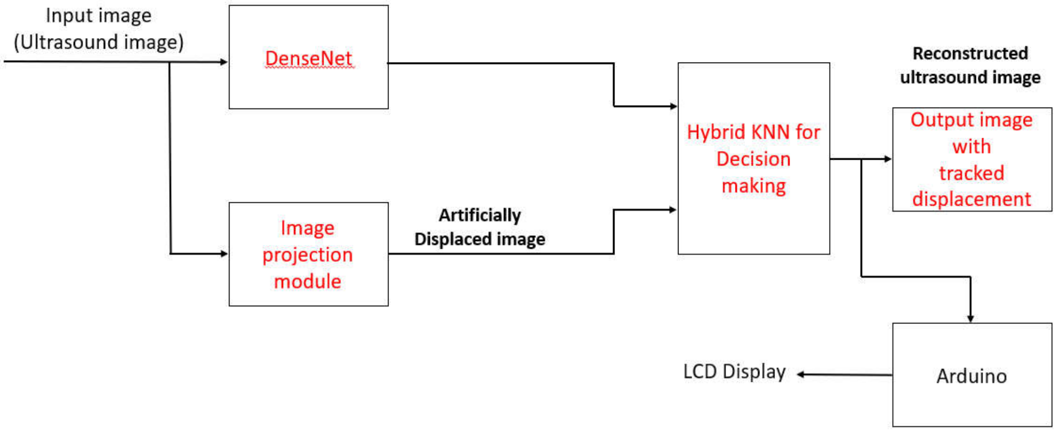

Figure 1 Block diagram of the proposed system

3.1. Densenet Architecture

DenseNet (Dense Convolutional Network) architecture [11] is one of the most efficient architectures to train, by using shorter connections between the layers and making deep learning deeper. DenseNet is a convolutional neural network where each layer is connected to all other layers that are deeper in the network. This is done to enable maximum information flow between the layers of the network. To preserve the feed-forward nature, each layer obtains its inputs from all the previous layers of output and also passes on its own feature maps to all the succeeding layers. Unlike ResNet, it does not combine features through summation but combines the features by concatenating them. So the 'xth' layer has 'x' inputs and consists of feature maps of all its preceding convolutional blocks. Its own feature maps are passed on to all the next 'X-x' layers. This introduces '(X(X+1))/2' connections in the network, rather than just 'X ' connections as in traditional deep learning architectures. Hence it requires only fewer parameters than traditional convolutional neural networks, so it is not necessary to learn insignificant feature maps. DenseNet consists of two important blocks. They are dense blocks and transition layers. The dense block contains a prespecified number of layers inside them. The output from that particular dense block is given to a transition layer and this layer is like one by one convolution followed by Max pooling to reduce the size of the feature maps. So the transition layer allows for max pooling, which typically leads to a reduction in the size of the feature maps.

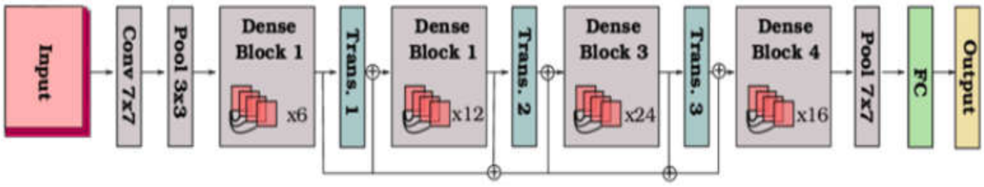

Figure 2 DenseNet Architecture

As given in Figure 2, the first two blocks are the convolution layer and the pooling layer, the preceding blocks are the transition layer and dense blocks are depicted.

3.2. Image Projection Module

In this module, a low-resolution ultrasound image from single plane wave acquisition is given as input. This image is projected to generate the projected image with respect to the input image to produce the artificial transformation of the tissues. This can be achieved with the help of DCT and IDCT algorithms [5]. The discrete cosine transform (DCT) converts data into the frequency domain. DCT represents data via summation of variable frequency cosine waves and captures only real components of the function. The inverse DCT(IDCT) reconstructs a sequence from its DCT coefficients. The IDCT decodes an image for the better suited to condensing in the spatial domain from a representation of the data. IDCT forms the basis for current image and video decompression standards as decoders. The fused image from the previous step is transformed using IDCT in order to get back the image in the spatial domain.

3.3. Back projection

The DCT transformed image can be projected to a maximum of 256 projections. Angle is given in terms of degrees. A mesh grid is applied to get the correct location of the reference pixel. Now the projection is done with the back projection method. Back projections are modeled as histograms to record how pixels of a given image match the distribution of pixels [7]. The projected image is fused with the DCT transformed image.

3.4. Displacement tracking

Several algorithms [9] are combined with the normal KNN algorithm to increase its performance. To track the displacement more efficiently hybrid KNN is used in the image fusion techniques to combine the trained input ultrasound image with the projected image. Image fusion is the technique of combining multiple images into one that preserves the important features. The wavelet transform is a better way to fuse images. If the basis functions match the interesting components of the image, then the fused image will contain the interesting components collected from all of the input images. The images can be combined in the transform domain by taking the maximum-amplitude coefficient at each coordinate. An inverse wavelet transform of the resulting coefficients then reconstructs the fused image. The masked images of both the DenseNet block and the projected image are fused to track the displacement that occurred in the image.

4. RESULTS AND DISCUSSION

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The system had been implemented with an accuracy of 95% and shows that it is immune to motion artifacts and enables accurate motion estimation at maximum frame rates. The lower the MSE value higher the performance. The MSE value of around 30 is achieved. The accepted PSNR value should be in the range of 30dB to 50dB. The achieved PSNR value is around 33dB. These results, shows that the system is working more precisely than the traditional system. Table 1 shows the comparison of the U-Net algorithm and DenseNet algorithm for the abdominal region image dataset.

Table 1 Comparison between U-Net and Dense-Net

	U-Net	Dense-Net
Accuracy	85%	95%
MSR	38	30
PSNR	45dB	33dB

4.1. Accuracy

The results of the numerical experiments are robust and translatable to experimental conditions. More specifically, motion artifacts were negligible in other experiments. Dataset of the input images is trained in such a way to gain more accuracy. Figure 3 gives the accuracy plot of DenseNet.

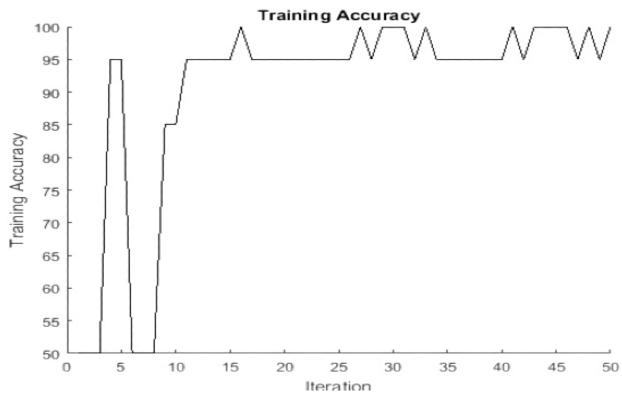

Figure 3 Accuracy Plot

4.2. MSE AND PSNR

MSE and PSNR is the most common estimator of image quality used to compare image compression quality. Figure 4 gives the MSE and PSNR values.

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MSE:    30.43
PSNR: 33.3315467 dB
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Figure 4 MSE and PSNR values

4.3. Displacement Track

After segmentation of a given image, it is split into global tracking where pixels are closely arranged, and local tracking where pixels are loosely arranged. This graph represents the attaining of peak value at some moment and then scrolling down to reach the value near zero. Figure 5 gives the relationship between the change in pixel value and displacement measured.

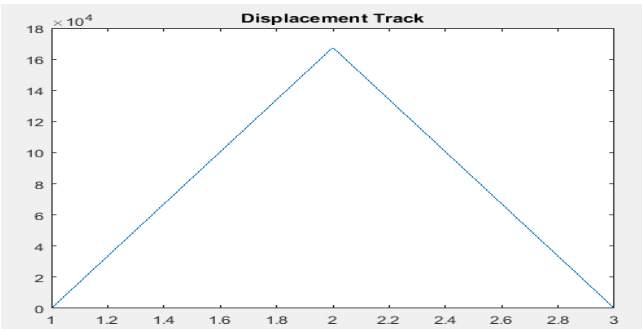

Figure 5 Change in pixel value with respect to displacement

4.4. Comparison of Input and Reconstructed Image

Since the network is trained using fewer samples overall training procedures require less memory. Typically, networks train faster with mini batches. This image is used to gain insight into qualitative features of the object without being deduced from a single plane of sight. Figure 6 gives the Reconstructed image with tracked displacement.

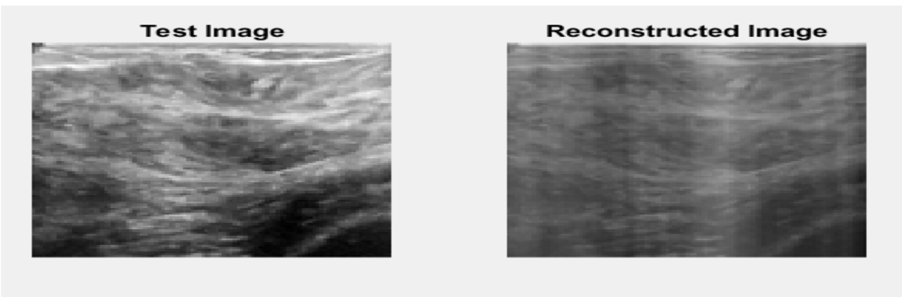

Figure 6 Reconstructed image with tracked displacement.

4.5. Pseudo Mapped Reconstructed Image

This result shows spectra of images with minimal introduction of artifacts and noise amplification. Figure 7 gives the Pseudo mapped reconstructed image with tracked displacement.

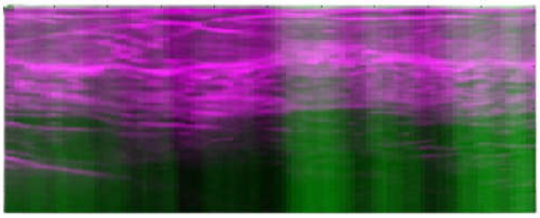

Figure 7 Pseudo mapped reconstructed image with tracked displacement

I. 5. CONCLUSION AND FUTURE SCOPE

The ultrasound image reconstruction method is implemented using Deep CNN, and HybridKNN, and the results are comparatively validated. Accuracy of 95% is achieved for reconstruction. This approach is immune to motion artifacts and enables accurate motion estimation at maximum frame rates even in highly heterogeneous tissues prone to strong diffraction artifacts. The proposed approach may thus unlock the full potential of ultrafast ultrasound, with direct applications to imaging modes that depend on accurate motion estimation at maximum frame rates. Combining block matching with a phase-zero search can obtain an accurate displacement field after first computing a rough displacement with block-matching that limits the error to no more than a half phase. The experimental results show that the proposed system can accurately and efficiently calculate the displacement field and effectively solve the error transmission problem when using prior information.

The proposed system can be designed and trained further for other medical imaging such as MRI and CT to reconstruct better medical images The system can be implemented in ultrasound scanning devices as software by improving the accuracy of reconstruction images using better CNN architecture.

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